determined, the difference in intensities between the red and blue data is determined etc. In all a six-dimensional feature set is derived from the responses from the four detectors for every segment of the image, so that every segment is represented by such a six-dimensional feature set.

[0050] To classify the document, individual classifiers on the feature sets extracted from each segment or region are devised. Each segment is individually considered in order that it can be classified, see step **14** of **FIG. 1**. In the present case, a mathematical function termed a one-class classifier is used. This type of classification is useful where information on only one class is available. It defines a boundary around the known class, so that samples that fall outside this boundary are deemed not to belong to the class. In the present example, the information that is available is the pattern and layout of the segments of genuine banknotes. Each of these is classified to define suitable boundaries. The resultant classifications for each segment are then used in order to create a reference template, see step **18** of **FIG. 1**, which can be used to validate or authenticate other banknotes. As part of the validation process, different segments may be given different levels of significance or weights. This is because certain segments of a banknote may be more difficult for fraudsters to copy and so may be more likely to indicate the presence of a counterfeit. This will be described in more detail later.

[0051] One-class classifiers are well known. Examples of these are described in "Support vector domain description" by Tax et al in Pattern Recognition Letters, 20(11-13) 1999 1191-1199; "One-class classification" by Tax, Technische Universiteit Delft Ph.D. Thesis, (2001) and "Support Vector Novelty Detection Applied to Jet Engine Vibration Spectra" by Hayton et al in Advances in Neural Information processing Systems **13**, MIT Press, 946-952, (2001). One example of a preferred classifier is based on a parametric D^2 test, as described in the book "Multivariate Statistical Methods" (third edition), by Morrison, McGraw-Hill Publishing Company, New York (1990). Another example of a suitable one-class classifier uses a semi-parametric test based on a mixture of Guassians, which semi-parametric test employs a bootstrap as described in "An Introduction to the Bootstrap" by Efron et al Chapman Hall/CRC Press LLC, Boca Raton, Fla. (1998). Each of these will be described in more detail.

[0052] A specific example of a classifier that can be used to devise a template and subsequently be used to validate currency will now be described. Consider N independent and identically distributed p-dimensional vector samples, in this case, the feature set for each segment of each banknote can be represented by $x_1, \ldots, x_N \in C$ with an underlying density function with parameters θ given as $p(x|\theta)$. The following hypothesis test is given for a new point x_{N+1} such that H_0: $x_{N+1} \in C$ vs H_1 $x_{N+1} \notin C$, where C denotes the region where the null hypothesis is true and is defined by $p(x|\theta)$ and the significance level of the test. Assuming that the distribution under the alternate hypothesis is uniform, then the standard log-likelihood ratio for the null and alternate hypothesis can be employed as a test statistic for the null-hypothesis. This test can be expressed as follows:

$$\lambda = \frac{\sup_{\theta\in\Theta} L_0(\theta)}{\sup_{\theta\in\Theta} L_1(\theta)} = \frac{\sup_{\theta} \prod_{n=1}^{N+1} p(x_n \mid \theta)}{\sup_{\theta} \prod_{n=1}^{N} p(x_n \mid \theta)}$$

[0053] This can be used as a statistic for the validation of a newly presented note. More specifically, a reference set of notes N is scanned and the six dimensional feature vectors are analyzed to determine a threshold value for λ for each segment of the note. The threshold value defines a boundary between what is acceptable and what is unacceptable. In practice, this threshold value defines a lower limit. If the value of the test statistic λ for a segment of test sample were below this, the test segment would be rejected. Likewise, if the value of the test statistic λ for a segment of test sample were above this, the segment would be accepted. Hence, in order to validate a test segment, it is scanned, segmented in a like manner to the segmentation used to define the reference template and a value for λ is determined for each segment. These values are compared with the reference threshold values for the corresponding segments to determine the validity of each of the segments.

[0054] One specific approach is to assume that the feature vectors for the banknote have a multi-variate Gaussian distribution. A test can then be applied to assess whether each point in a sample shares a common mean. Examples of this type of test are described in more detail in the book "Multivariate Statistical Methods" (third edition), by Morrison, McGraw-Hill Publishing Company, New York (1990). As a specific example of a suitable test, consider N independent and identically distributed p-dimensional vector samples $x_1, \ldots, x_N$ from a multi-variate normal distribution with mean μ and covariance C, whose sample estimates are $\hat{\mu}_N$ and $\hat{C}_N$. From this sample consider a random selection denoted as x_0. For this selection the associated squares Mahalanobis distance is:

$$D^2=(x_0-\hat{\mu}_N)^T\hat{C}_N^{-1}(x_0-\hat{\mu}_N)$$

[0055] This can be shown to be distributed as a central F-distribution with p and N-p-1 degrees of freedom by:

$$F = \frac{(N-p-1)ND^2}{p(N-1)^2 - NpD^2}$$

[0056] Then, the null-hypothesis of a common population mean vector for x_0 and the remaining x_i will be rejected if:

$$F>F_{\alpha;p,N-p-1}$$

[0057] where α is a pre-set significance level for the test and $F_{\alpha,p,N-p-1}$ is the upper α**100** % point of the F-distribution with (p,N−p−1) degrees of freedom, so that by using this threshold α times 100% genuine samples will be rejected. The incremental estimates of the mean and covariance $\hat{\mu}_N$ and $\hat{C}_N$ respectively are as follows:

$$\hat{\mu}_{N+1} = \frac{1}{N+1}\{N\hat{\mu} + x_{N+1}\}$$